



Scenario-Based Cellular Automata and Artificial Neural Networks in Urban Growth Modeling

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Highlights

- This paper focuses on scenario-based urban growth modelling in terms of complex relationships.
- The development scenarios used in the research are based on real-life urban strategies.
- The growth of Izmir is simulated with Cellular Automata and Artificial Neural Networks.

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Abstract

The speed at which cities are growing and developing today cannot be disregarded. Human activities and natural causes are both contributors to urban growth. The relationship between these factors is complex and the complexity makes it difficult for the human mind alone to understand cities. A model that helps reveal the complexity is needed for urban studies. Main objective of this study is to understand the effects of urban planning strategies on the future of the city by utilizing a Cellular Automata and Artificial Neural Networks based simulation model. Driving factors of urban growth according to development scenarios were used in the simulation process. Six different development scenarios were formulated according to the strategic plan of Izmir. Land use and driving factor data used in simulating scenarios were acquired from EarthExplorer and OpenStreetMap databases, and produced in QGIS. Future Land Use Simulation Model (FLUS) based on Cellular Automata (CA) and Artificial Neural Networks (ANN) was used. The results were assessed both by using FRAGSTATS which helped calculate fractal dimensions and visual analysis. Fractal dimension results of each scenario showed that the simulation model respected the overall urban complexity. A closer look at each scenario indicated the diverse local growth possibilities for different scenarios. The results show that urban simulation models when used as decision support tools promise a more inclusive and explicit planning process.

1. INTRODUCTION

Urban development is a force which needs to be handled with consideration of the complex relationships that contribute to its speed. These complex relationships, which are usually ignored, cause the change in the city; whether this change is degrowth or growth. Due to a number of causes, urban growth and degrowth patterns have repeated irregularly in history [1]. Urban planning provides answers to these changes. However, planning struggles to catch up with the changing urban dynamics. As a consequence of this struggle, urban complexity is ignored. Computational methods integrated to urban issues emerge as a possible solution to the aforementioned problem. Still, computational approaches are not employed extensively, especially in real life urban planning applications. Lack of model expertise and models not being exposed to the decision makers are the causes of this distance. However, as the sciences evolve, the way we understand the cities change, and both the urban theories and the models are affected by this. Thus, the gap between the models and urban theories decreases.

One urban simulation method that helps build the bridge between the models and urban studies is cellular automata. Simple in essence, but complex as a whole system, it is employed extensively in urban studies. It attracts attention in terms of application to geographic problems because of its spatial nature and its ability to produce very complex forms with very simple rules. As human factor causes complexity, the model should satisfy the stochasticity that will reflect the human-decision making process. Furthermore,

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stochasticity incorporated into the model may reflect the individual and collective activities happening simultaneously in the city [2]. Cellular automata meets the requirement of stochasticity with neighborhood rules, suitability, accessibility and weighted functions. Unchanging features (rivers, lakes, parks, etc.) and suitability values (slope, accessibility, soil type, etc.) make it possible to model cities in high resolution [3].

With the increasing interest in cellular automata based simulation models and its widespread use in diverse studies, models which mimic simplicity and complexity have gradually developed and branched out. Extending neighborhood window [3], irregular cells [4,5], defining neighborhood window as network [6], incorporating artificial neural networks [7], fuzzy transition rules [8] and applying genetic algorithms [9] are small examples of the diverse studies based just on cellular automata.

It is important to remember that urban simulation models don't aim to find definite answers. On the contrary, user tendencies are celebrated as richness in the field. These models are used as spatial decision support tools, which help unfold what the city hides. Camacho et al. [10] defines the aim of the simulation models as determining possible development paths, not as predicting the future conditions of the city. Determining possible development paths means understanding the effects of the development beforehand and predicting the possible urban futures under different planning scenarios. Since cellular automata approach is simulation based, it doesn't explain the reason for urban growth, but imitates it [11]. The reasons for urban growth, growth patterns and the effects of growth are understood by interpreting the simulation rules and their results based on the scenario.

This study derives from the need to understand the causes of urban growth affected by the complex relationships. It is more important than ever to predict how urban areas will be affected under any intervention and plan livable cities according to this prediction. In the light of this need, the aim is to find out the implications of planning decisions on the future of the city by utilizing a model born from complexity. The questions this study asks are how urban development affects the future of the city and what the driving factors of urban strategies are. Following up questions are what the role of driving factors in urban models is and how they affect the model results. Top-down (planned) and bottom-up (emergent) urban factors must find their correspondence in the urban simulation model they are to be applied. This study utilizes an urban simulation model called FLUS, Future Land Use Simulation [12], which brings together cellular automata imitating bottom-up emergent factors and artificial neural networks as the top-down method, in a case based on the city of Izmir. The reasons for selecting Izmir for this study are that Izmir is the third-largest city in Turkey and is expected to keep this place in the future, and there isn't any study conducted on Izmir using this method.

2. LITERATURE REVIEW ON URBAN SIMULATION MODELS

There is a variety of urban simulation models based on cellular automata. Where initial models developed in the 1970s were based on dynamic cellular automata theories [13], current models have become more sophisticated with the computer technologies advancing. The models have incorporated various additional methods to cellular automata.

Table 1 shows the urban simulation models developed in the last thirty-five years. As is seen from the table, there are only a small number of models which utilize one method. The methods supporting cellular automata are Markov Chain, Multi Objective Land Use Allocation, NASZ (Neighborhood – Accessibility – Suitability – Zoning), Multi Criteria Evaluation, Artificial Neural Networks, statistics and heuristics. The earliest models LCM and METRONAMICA are both powerful yet paid software. LCM has a high accuracy rate due to artificial neural networks [14]. CLUE and its sequent Dyna-clue aim to see the implications of different scenarios [15]. DINAMICA EGO focuses more on environmental change [16]. SLEUTH is widely used as it is open source and easy to improve. However, the cell states are only limited to urban and non-urban [17]. SIMLANDER, also, is limited to two cell states [18]. APoLus, which is developed from SIMLANDER, includes multiple cell states and additionally planning decisions [19]. LucSim is an experimental model focusing on transition potential based on cellular automata principles [20]. UrbanCA incorporates spatial and non-spatial dynamics as well as heuristics [21]. FLUS (Future Land Use Simulation), which is the model used in this study, is based on cellular automata just like the other models

mentioned. Similar to LCM, its strength is in the use of artificial neural networks. Moreover, it is free and easy to use. The model allows the user to simulate different scenarios with multiple cell states.

Table 1. Urban simulation models developed in the last 35 years

Model Name	Year	Developers	Language	Method(s)
LCM Terrset (IDRISI)	1987	J.Ronald Eastman-Clark Labs	C++, Python, Delphi	Markov Chain, Multi Objective Land Allocation, Artificial Neural Networks
METRONAMICA	1992	Research Institute for Knowledge Systems		NASZ (Neighborhood – Accessibility – Suitability – Zoning)
CLUE	1996	Veldkamp & Fresco	PASCAL	Multi Objective Land Allocation
SLEUTH	1997	Clarke, Hoppen & Gaydos	C under UNIX	Constraint Cellular Automata
DINAMICA EGO	1998-2015	Soares-Filho BS	C++, Java	Multi Criteria Evaluation
Dyna-clue	2009	Verburg & Overmars	DYNA	Multi Objective Land Allocation
SIMLANDER	2013	Hewitt, Diaz Pacheco & Moya Gomez	R	NASZ
LUCSIM	2015	Antoni & Vuidel	JAVA 8	Markov Chain
APoLuS	2015	Hewitt	R	NASZ
FLUS GeoSOS	2017	Liu, Liang, Li, Xu, Ou, Chen, Li, Wang & Pei	C++	Multi Objective Land Allocation, Artificial Neural Networks
urbanCA	2018	Tong & Feng	R+ARCGIS	Statistics + Heuristics

3. MATERIAL AND METHOD

Six scenarios for simulation are built upon the analysis of Izmir's strategic planning decisions. The scenarios are classified as base scenario, transportation scenario, agricultural, industrial, tourism and regional scenarios. Working with scenarios helps deviate from the traditional thinking patterns. Using simulation models advancing from a single standpoint which produces highly accurate images causes blindness in the results, as it shows one possible future of the city rather than revealing its alternative futures. While it is necessary to use different factors while creating the scenarios, it is important to use common variables in order to ensure the comparison of the scenarios [22].

Environmental characteristics, neighborhood relations, spatial qualities and planning policies are detailed further as the driving factors. Individual likes and needs make location based decisions more complex and intricate. For this reason, individual preferences and socio-economic factors are kept out of scope and will be incorporated in the further studies. According to the studies focusing on the quality and quantity of driving factors, using limited but relevant factors instead of many of them proved to be more effective as the number increases, accuracy of the simulation decreases [1,23,24].

Geographic Information Systems (GIS) are essential tools for collecting spatial data, visualizing and analyzing existing data, and extracting new knowledge from this process. As worldwide information spreads all around the world with the internet, accessing and sharing data by using GIS gets easier. Thus, spatial data become increasingly detailed and complex. GIS based data occupies a large space and is the core of the simulations particularly in modeling urban dynamics. In this study, QGIS, which is a free and open-source GIS software, is used. Land use data is acquired through Semi-Automatic Classification [25] plugin in QGIS. United States Geological Survey's (USGS) Earth Explorer and Overpass API – Open Street Map (OSM) databases are used for obtaining driving factor data. Probability of occurrence of each land use type is calculated with FLUS – Artificial Neural Network module. Six different scenarios are then simulated with the Cellular Automata module using these probabilities. Simulation results are compared for each district in the city. Besides visual analysis and interpretation of the results, quantitative results such as land use area ratios, total patches and fractal dimensions are compared with the help of FRAGSTATS [26].

3.1. Study Area

Izmir, with the population of 4,3 million people, is the third-largest city in Turkey according to the 2019 statistics. The entire population of Izmir is urban. It is seen that Izmir, which is also at the forefront in terms of population growth rate, maintains its third place in the 2023 population projection [27]. The development of the city between 1990 and 2019 in terms of built area is shown in Figure 1.

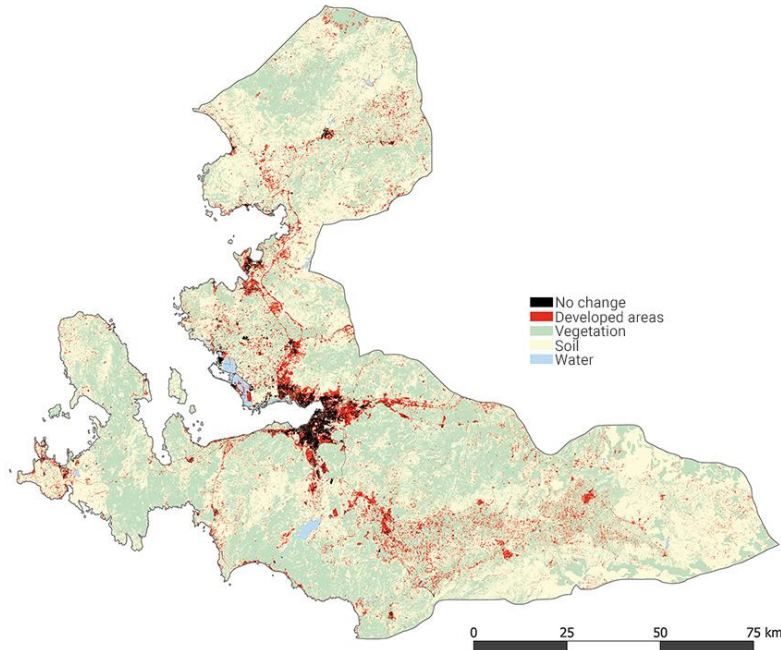


Figure 1. Izmir's urban development between 1990 and 2019

Izmir Development Agency conducted a series of studies in 2012 and 2013 in order to identify and analyze recent and future problems caused by population growth and plan the development of the city according to its identity which was created by including all the stakeholders. As a result of this study, they released the 2014-2023 Izmir Regional Report [28]. The report shows that the regional plan is shaped around three goals: Strong economy, high quality of life and strong society. The common point of these three goals is that they all focus on sectors such as agriculture, industry, tourism, health and entrepreneurship. The spatial development of the city is also planned according to the concentration trends of these sectors.

Industry and agriculture sectors stand out in the regional development. Both industrial and agricultural belts cover the south, west, and north of the city. The development of the south of the city, which covers the districts of Aliaga, Dikili and Bergama, is considered industry oriented whereas the north of the city, which consists of the districts of Bayindir, Tire and Odemis, is agriculture oriented. Agriculture also continues to be encouraged in the whole city, particularly in the periphery. Industry zones are more compact in comparison to the agriculture zones which overflow into the provincial borders. City center, on the other hand, continues its service oriented development.

According to the strategic planning summarized above, the districts are classified as agricultural, industrial, tourism and regional development centers (Figure 2). Torbali and Bergama are the development focuses of three different sectors which are agriculture, industry in common and regional and tourism respectively. Dikili has been specified as an industry and tourism focus in the north, and Urla as a regional and tourism center in the southwest. While Menderes and Aliaga are the focus of agriculture and industry, Kinik, Bayindir, Tire, Odemis, Kiraz and Beydag have been determined as development centers focused on agriculture and tourism. It is observed that especially the coastal districts are tourism oriented.

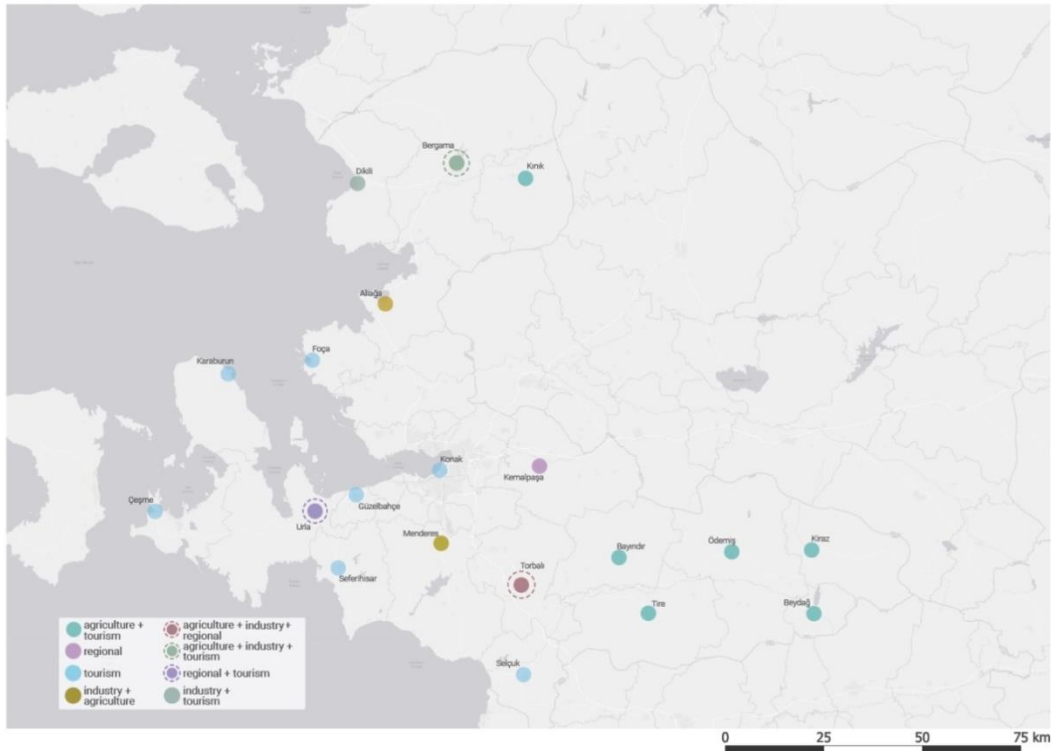


Figure 2. Districts of Izmir and their sectoral development focuses

3.2. Simulation Scenarios

The mutual driving factors used in all six scenarios are land data and protected areas. Land data consists of constant physical factors which are digital elevation model, slope and aspect. Protected areas are assumed to be unchanging due to their inherent characteristics and their protection under law. After deciding on the mutual data of all scenarios, the first step in scenario based simulations is to determine the base scenario. Base scenario uses the existing land and transportation data without any interpretation. It helps the modeler see how the urban development will proceed without any prominent factors. The driving factors of the base scenario are the main, primary and secondary roads, ports, aspect, slope and digital elevation model.

Transportation scenario is specified under the assumption that only existing and planned roads will have higher impact on the development without any additional point based weight. This scenario is built upon the base scenario by adding tertiary, planned roads and paths under construction.

Agricultural, industrial, tourism and regional scenarios are determined according to the information in the report prepared by Izmir Development Agency (IZKA). The development points are explained in the previous section. Different data specific to each scenario are incorporated into the respective simulations. Wetlands, namely rivers and streams, existing farming areas and greenhouses are added to the data set for agricultural scenario. In the industrial scenario, it is important to consider the tendency of industrial zone clustering, by incorporating access to organized industrial zones and power sources. The ports are not considered as a driving factor for both cases as agricultural areas do not have a direct relationship with the port and Izmir Port is not substantially relevant for industrial zones except for cargo ships which anchor in only one port. The difference in the tourism scenario is the inclusion of the ports and tourist attractions. Sea tourism is prioritized as Izmir is considered a port city, and the regional scenario is set up with this consideration.

3.3. Land Use Classification

The common point simulation models and studies have is that they analyze and compute land use change and patterns. As the studies are specifically the focus of environmental sciences and geography, they are

based on land use and land cover change. Humans and their actions affect the land and consequently shape the global environmental changes; therefore, understanding the workings and causes of land use change matters in terms of understanding environmental changes [29].

In order to produce land use data for Izmir, first remote sensing (RS) images are selected for land use classification. RS data are downloaded through Semi-Automatic Classification (SCP) Plugin for QGIS. SCP is a free plugin which calculates supervised or unsupervised semi-automatic classification of remote sensing images. By defining the coordinates of the analysis area it is possible to download related images, pre- and post-process them and make raster calculations on SCP. SCP could reach the 1990 RS images of Izmir as the earliest data. So as to maintain the quality of the 1990 and 2019 land use classification, the images which had 0% cloud cover are selected. Images are then calibrated. Classification of land use and land cover is produced by the Maximum Likelihood algorithm. This process requires creating land use classes and selecting a sufficient amount of training data. It is possible to preview results, and this helps determine when the training data is adequate. Still, each class requires a large amount of training input. Soil and built area demand more data than vegetation and water, as their spectral distances are relatively close. After classification is completed, accuracy for both 1990 and 2019 land use classification is tested. The classification performance is calculated by confusion matrix using training data as reference. Accuracy rates for 1990 and 2019 are 98.409% and 95.182% respectively. Kappa coefficients which reflect the classifier's performance are 0.978 for 1990 and 0.933 for 2019.

3.4. Driving Factors

Digital Elevation Model (DEM) helps obtain various land data. United States Geological Survey (USGS) offers free to use geospatial datasets on Earth Explorer database. For this study, high resolution SRTM-1 digital elevation model is acquired through Earth Explorer. Slope and aspect data are extracted from DEM in QGIS.

Overpass API is an online interface using OpenStreetMap (OSM) database which has a diversity of location based features. The client queries and retrieves the data they need to access. Existing and planned roads, ports, rivers, power plants, greenhouses and tourist attractions have all been accessed via the Overpass API. However, Overpass API falls short in aspects that haven't been fed into the database. In this case, the results acquired from the API for the protected areas aren't enough. API shows only Gediz Delta, where Izmir Bird Paradise is located. According to the GeoData database of the Ministry of Agriculture and Forestry and the information provided by the Izmir Provincial Directorate of Culture and Tourism, there are eight nature parks and two wildlife preservation areas in the city. These parks and areas are included for an accurate and extensive dataset. Additionally, historical ruins, archeological sites, mining areas and military lands acquired from the Overpass API have been designated as protected areas which are not undergone any calculations, used as mask layer which indicates areas that won't be simulated in cellular automata.

Taking Tobler's law which suggests the things that are close are more related to each other, all the data that constitute human, nature and transportation factors are processed with Euclidean distance calculation. Euclidean distance expresses the linear distance between two points. In GIS, it translates as a cell's relation to a source in a linear distance. Euclidean distance calculations are made via Grass GIS, which is integrated with QGIS.

3.5. Cellular Automata and Artificial Neural Networks Based Simulation Model

Future Land Use Simulation (FLUS) model, which is both stand-alone software and is available for use in GeoSOS, is an urban model that simulates different scenarios with cellular automata and artificial neural networks. Cellular automata (CA) is explained in the first chapter as a method which is popular in urban studies. Artificial neural networks (ANN) are mentioned briefly as an additional method to CA models. ANN comes forward in dealing with geospatial data. The size of geospatial data has brought about the quest for effective methods in processing and analyzing it. Performance of ANN in geospatial calculations of different scales and resolutions is accepted as satisfactory [30]. Classification, change detection, clustering, prediction and forecasting are main applications of ANN in geospatial studies [31]. According to the

literature studies and experiments, FLUS is selected for its ease of use, its incorporation of the artificial neural networks and the speed of the simulation.

FLUS enables simulating multi-class land use scenarios by combining human actions and natural effects. The model is presented as a tool to calculate the development possibilities within the city by finding the complex relationships between human and nature factors with the help of artificial neural networks, combined and enriched with cellular automata which make spatial simulations. ANN calculates probability of occurrence in terms of historic land use and driving factors that affect land development. Self-adaptive inertia and competition mechanism integrated into CA imitate real-world relationships between land use classes. The initial state of the cell turns into another state or remains the same according to the total of the probability of occurrence and CA rules, or it changes randomly under roulette wheel selection which translates the stochasticity into the model. Improvements made upon fundamental CA simulation are processing social and natural data at the same time with ANN, avoiding discrepancy resultant of including previous years' land use data by using only the input of the latest year, and considering interaction and competition between each land use class [12,32].

3.6. Scenario Based Simulation

The land use data of two different years and scenario-based data are resampled to the same resolution and prepared for the simulation model. All the driving factors are aligned with 1990 and 2019 land use data maps. All the datasets are at 30x30 m² resolution and have X:6868, Y:5661 cells. Since the study aims to observe how the city will grow according to the urban development scenarios with a simulation model, and to see how this development will differ only by changing the data sets in the scenarios, calculating land use demand according to the scenarios is excluded. Figure 3 represents the flowchart of the simulation model which consists of data preparation in GIS, model training with ANN, and CA based simulation.

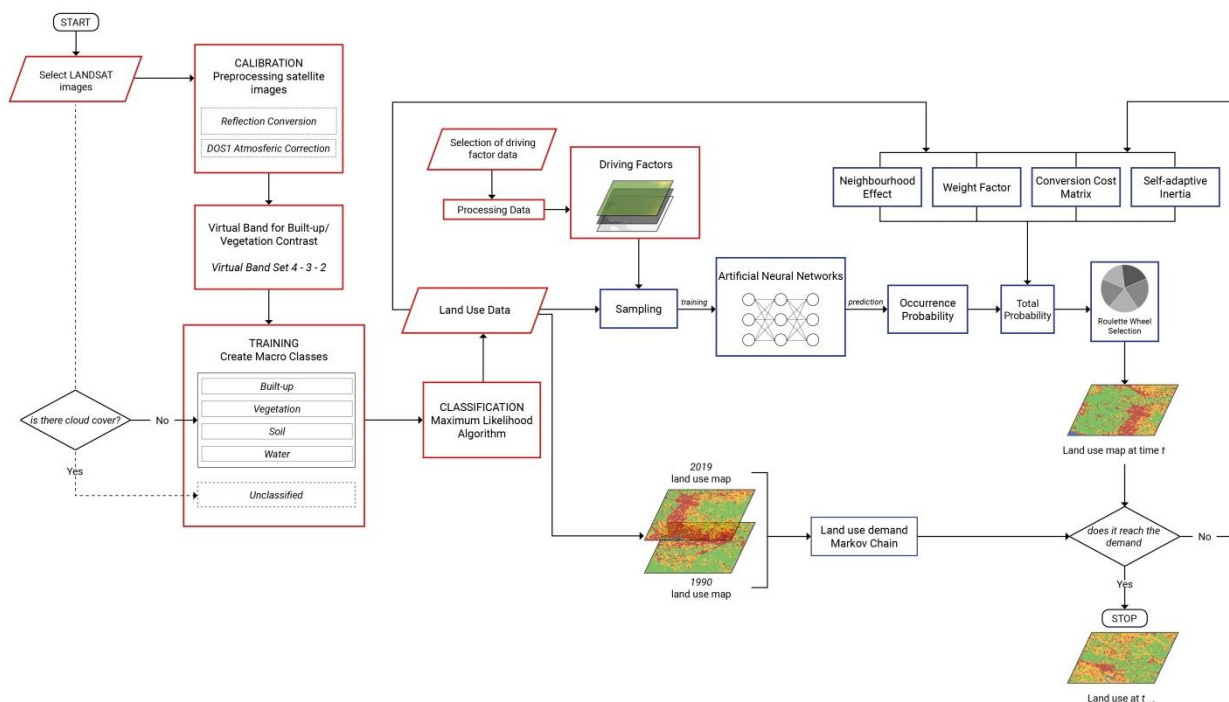


Figure 3. Flowchart of the simulation model

FLUS requires the number of cells of each land use class for the year to be simulated. This number is calculated quickly by the Markov Chain module in FLUS. Land use data for 1990 and 2019 are given to the Markov model as inputs, which helps calculate every other 29-year period. As it is not recommended to simulate long intervals, the land use demand for the first 29-year period, i.e. 2048 estimated, is calculated. However, this calculation made an interesting case explicit where the number of cells of class 1, water, increased considerably since a couple of dam lakes were built after 1990. As this kind of situation can't be

predicted and there aren't any plans disclosed to the public regarding more dam lakes, the number of cells belonging to the water class is kept the same as 2019. The residual cells are distributed among other classes.

After determining the number of cells for simulation, probability of occurrence for each class has to be calculated with ANN using driving factors. The number of neurons in the hidden layer of ANN is determined according to the number of driving factors of the scenario to be simulated. The number of neurons in the hidden layer should be the sum of twice the number of inputs and 1 ($2x+1$). However, the studies on ANN show that one third of two times the number of inputs ($2x/3$) give efficient and faster results. One other thing to consider is to keep the number of neurons less than two times the number of input neurons. The number of hidden layer neurons should be between the numbers of neurons in the input and output layers. Numbers of neurons according to the number of driving factors of each scenario are given in Table 2.

Table 2. Scenario based driving factors and hidden layer neuron counts

Scenario	Driving Factor 1	Driving Factor 2	Driving Factor 3	Driving Factor 4	Driving Factor 5	Driving Factor 6	Driving Factor 7	Hidden layer neuron count	
Base	DEM	Slope	Aspect	Roads	Ports			5	
Transportation				All the roads inc. tertiary	Ports	Planned roads			5
Agriculture					Greenhouses	Agriculture focus points	Streams		6
Industry					Organized industry areas	Industry focus points	Power plants		6
Tourism					Ports	Tourism focus points	Attraction points		6
Regional					Ports	Regional focus points			5

Driving factors should be normalized to the range [0, 1] in the FLUS-ANN module if not already. 2% of the dataset is selected for training. This means that 777595 of a total of 38879748 cells in the 6868x5661 data set are selected for training and testing. Sigmoid function is used as the activation function to normalize the output layers.

In the simulation settings neighborhood effect, neighborhood weight of each land class, transformation matrix and land use demand numbers obtained from Markov Chain are indicated. The prior experiments have shown that the 3x3 Moore neighborhood gives more appropriate results in the development, especially for the city of Izmir, compared to the larger-scale neighborhood effects. For this reason, all scenarios have been simulated according to the 3x3 neighborhood effect. Neighborhood weights, transformation matrix and land use demand numbers are also kept the same for all scenarios as the aim is to see the impact of determining factors on the city on a scenario basis. Table 3 shows the transformation matrix of land classes. If [1], a land class can transform into the other class; if [0], it cannot transform. According to the matrix, water and built area stays the same, vegetation and soil can transform into other classes except water. Neighborhood weights are determined heuristically. The prediction is that the built area will have a greater weight in the development. As Izmir is classified as a port, tourism and agriculture city, it is assumed that water and vegetation will have a higher impact than soil.

Table 3. Land use class transformation matrix

	Water	Built area	Vegetation	Soil
Water	1	0	0	0
Built area	0	1	0	0
Vegetation	0	1	1	1
Soil	0	1	1	1

4. THE RESEARCH FINDINGS AND RESULTS

Local changes in urban growth based on each scenario can be seen in the district based results. Figures 4, 5 and 6 are given as samples of the local results. The interpretation of simulation results of three different districts are summarized in Table 4. Accordingly, the effect of roads can be easily observed, especially in the base scenario which doesn't have any growth focus and in transportation scenario where roads have a significant importance. The proximity to greenhouses carries substantial weight in the agricultural scenario. In industrial scenario, unexpected developments or non-development situations are noticed apart from the effects of driving factors. It is also observed that the effect of ports is more evident in tourism and regional scenarios.

Table 4. Interpretation of simulation results of three different districts according to scenarios

Districts	Base	Transportation	Agriculture	Industry	Tourism	Regional
Aliaga			Growth towards the north (greenhouses). Development in the North-South axis as it is between two rivers.	Concentration around transport channels. Growth towards OIZs in the north and south.		Growth to the west (harbors) and south (to the regional foci).
Bergama		Development around the planned road.		There is a region where there is no development due to randomness.		Except for the centers and roads, there is no development.
Urla				The scenario with the least impact.	More development than others as it is the focus of tourism.	Since it is a regional focus, the most obvious development and emergence is seen.

The big picture shows that the growth in regional scenario has decreased or not even happened towards the provincial borders. The reasons for this are that the ports, which are the driving factors of the regional scenario, are located on the coastline and the regional growth centers are closer to the city center than the borders. It is possible to combine this scenario with other scenarios in future studies.

The base scenario and the transportation scenario do not differ significantly in terms of growth direction and pattern. The difference in the transportation scenario is the agglomeration observed around the new roads under construction or planned to be built. Simulating these two scenarios is effective in seeing the possibilities of not having any driving factors other than the base factors in urban growth. The results of agricultural, industrial and tourism scenarios are more visually informative. The obvious difference between the driving factors has shown varying or increasing growth specific to the scenario for each influence area in the city.

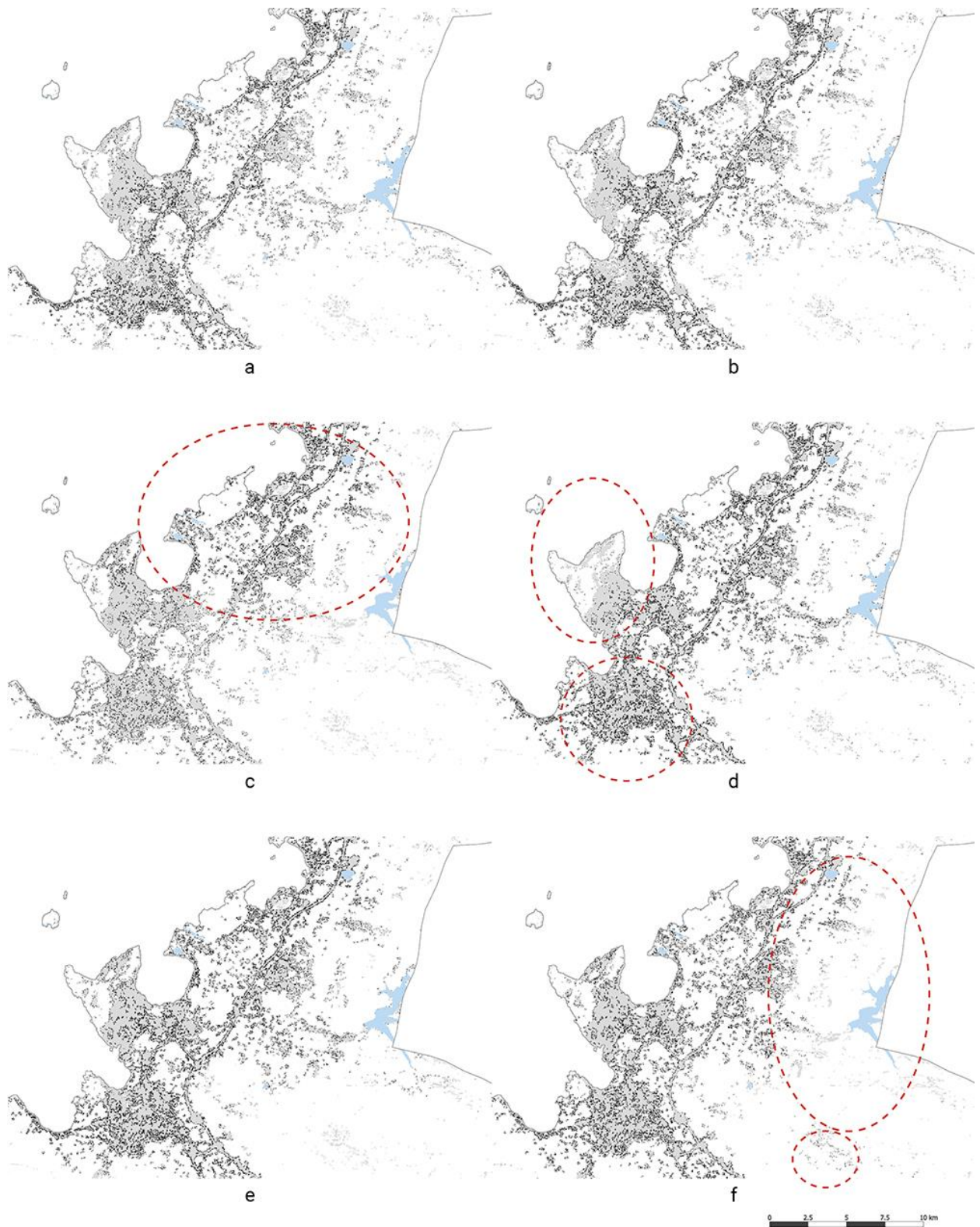


Figure 4. Scenario based development of Aliaga, a) Base scenario; b) Transportation; c) Agriculture; d) Industry; e) Tourism; f) Regional

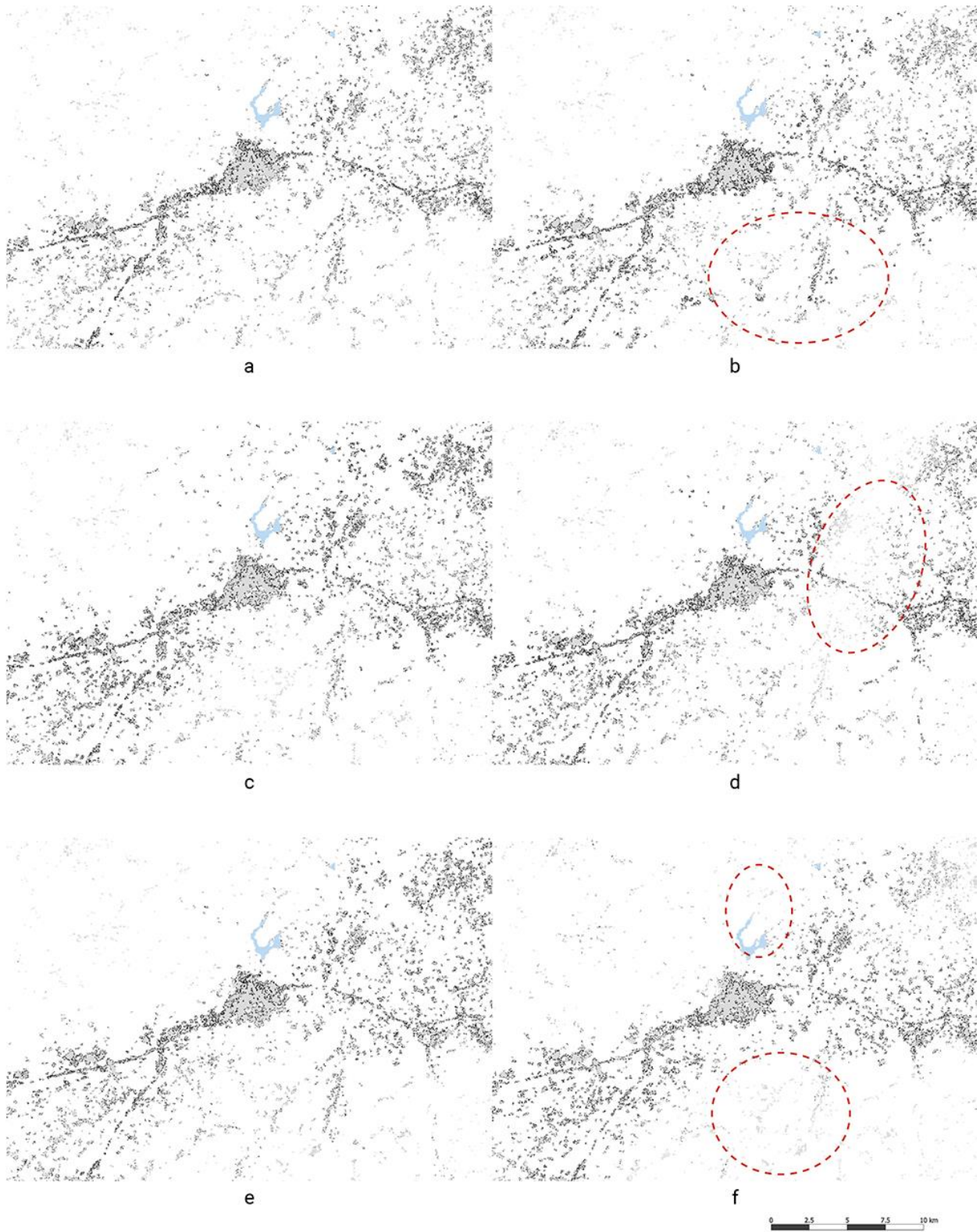


Figure 5. Scenario based development of Bergama, a) Base scenario; b) Transportation; c) Agriculture; d) Industry; e) Tourism; f) Regional

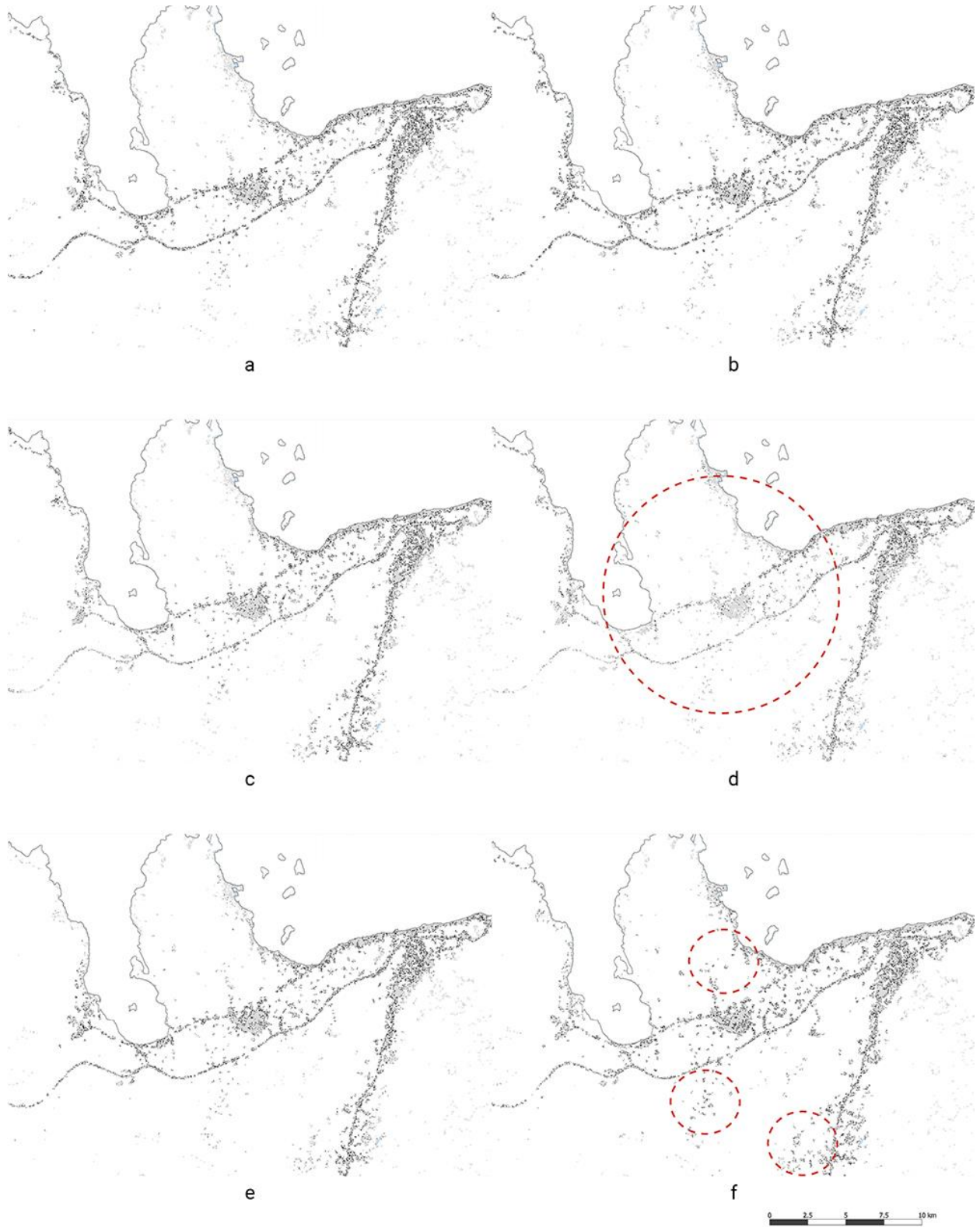


Figure 6. Scenario based development of Urla, a) Base scenario; b) Transportation; c) Agriculture; d) Industry; e) Tourism; f) Regional

The results are analyzed quantitatively in the scale of land class. FRAGSTATS [26] is a spatial metrics tool used for quantitative analysis. Primarily a tool for measuring the landscape, FRAGSTATS is also frequently used in urban development studies [33]. Validity tests for simulation models are generally performed on the accuracy of the location of the cells. However, the results are very different from the actual growth

patterns and the validity test results are high in terms of the distribution of cells [34]. Therefore, the conventional validity tests are not found appropriate in the scope of this study, as the research focuses on the urban growth possibilities under different scenarios for the same year. The preferred method is to compare the spatial pattern and complexity of the simulation results in order to see the similarity of them in terms of urban planning decisions and to test the consistency of the simulation model. Table 5 shows the total area and ratios of land classes.

Table 5. Total area and ratios of land use classes

Class	Total area (ha)				Ratio of Class			
	Water	Built area	Vegetation	Soil	Water	Built area	Vegetation	Soil
1990	3828,51	46846,62	475656,39	709066,35	0,3099	3,7934	38,5017	57,3950
2019	9061,29	100103,85	488919,60	636473,25	0,7340	8,1085	39,6028	51,5547
Scenario Simulation Results	9061,29	123509,97	482626,53	619360,20	0,7340	10,0044	39,0931	50,1686

The number of patches of each land class shown in Table 6 represents the urban fragmentation. Accordingly, the development between 1990 and 2019 increased the division within land classes. The fragmentation decreases in the built area, but increases in the vegetation and soil classes. Cellular automata and competition mechanism used in the model, especially neighborhood effect and weight values, are possibly the reasons for the fragmentation results. The absence of sudden increases or decreases in different scenarios supports this argument.

Table 6. Total number of patches of each land use class

	Water	Built area	Vegetation	Soil
1990	1263	16428	24556	22680
2019	1379	41492	32919	33642
Base	1379	34893	37701	44037
Transportation	1379	34772	37806	44437
Agriculture	1379	34732	37941	44918
Industry	1379	34930	37556	43781
Tourism	1379	34584	37751	44660
Regional	1379	34544	38019	45499

The fractal dimension, which stands out as a measure of complexity, has been an important tool in explaining the irregularity of the urban fabric in urban analyses. The larger the fractal value in the range of $1 \leq x \leq 2$ is, the more complex the shapes are. The area-perimeter fractal dimensions of the simulation results of this study are given in Table 7. The urban development from 1990 to 2019 happened in a way that the

fractal values of all classes decreased. In the simulation results, the fractal value of the built area increased, and the rest, except water class which remained constant, decreased. The results compared within the scenario based simulations are very close, almost the same, in value.

Table 7. Area-perimeter fractal dimensions of each land use classes

	Water	Built area	Vegetation	Soil
1990	1,4951	1,6114	1,5534	1,5734
2019	1,4401	1,5363	1,4987	1,5514
Base	1,4401	1,5654	1,4625	1,4789
Transportation	1,4401	1,5615	1,4605	1,4764
Agriculture	1,4401	1,5618	1,4612	1,4778
Industry	1,4401	1,5620	1,4626	1,4781
Tourism	1,4401	1,5653	1,4622	1,4784
Regional	1,4401	1,5578	1,4603	1,4770

Differences in fractal dimensions as percentage are shown in Table 8. The difference, which can also be represented as percentage (%), between two results is used to interpret the similarity; the lesser the ratio, the higher the similarity [35,36]. In this case, differences are categorized as differences between 1990 and 2019, 2019 and the simulated scenario specific to land use classes. According to the differences between 1990 and 2019, the built area has changed the most, where soil and vegetation stayed relatively similar. Differences between 2019 and the scenario simulations, on the other hand, suggest less change in built area and vegetation compared to soil. Also, there is no significant difference between scenarios. The results show that the change in driving factors in each scenario doesn't cause a change in the fractal dimension in the urban scale. The change is expected to increase on a more local scale.

Table 8. Differences as percentage (%) between fractal dimensions

Difference	Water	Built area	Vegetation	Soil
1990 – 2019	5,5%	7,51%	5,47%	2,2%
2019 – Base		2,91%	3,63%	7,25%
2019 – Transportation		2,52%	3,82%	7,5%
2019 – Agriculture		2,55%	3,75%	7,36%
2019 – Industry		2,57%	3,61%	7,33%
2019 – Tourism		2,9%	3,65%	7,3%
2019 – Regional		2,15%	3,84%	7,44%

As understood from the numbers, the change in driving factors in the simulation scenarios doesn't cause a large fluctuation in an urban development study of this scale. The apparent reason for this is that the land

use demands are kept constant, and the simulated period is not large enough to make a big difference between scenarios in terms of spatial pattern. The probability of occurrence data generated by training ANN contributes to this. ANN enables modeling the urban development in accordance with the existing fabric, as it can handle the nonlinear character of the geospatial in a way that it leads to the most appropriate result in the whole data set. Completely different results can be obtained in a model that incorporates different methods. The differences seen at the local scale when zoomed in to the map indicate that the scale also has an effect on the complexity in urban development.

5. DISCUSSION

The definition of what the city is, what its layers are, and which forces affect the city are complex and diverse. This complexity makes it difficult to create a holistic framework of urban growth. Each study is specific to the definition of the 'city' it makes and is carried out on. For this reason, analysis and simulation qualities of each study change. The simulation settings, land use data, driving factors and the methods applied are customized. Since the city is the subject of different disciplines and cannot fit into a single discipline, simulation studies are also carried out interdisciplinarily. The application of simulation models requires a deep understanding of both urban theory and simulations. The fact, that a cause-effect relationship can be established between simulation results and planning decisions, shows that urban simulation models are effective auxiliary tools for planning.

Comparing all the results shows that working with scenarios produces many possibilities in the city. When driving factors derived from planning decisions and strategies are customized according to scenarios, their effects on the simulation results can be visibly distinguished. Using mutual data in scenarios makes it easier to see the impact of other factors and compare the results accordingly. The differences between scenarios can be observed more clearly by keeping the factors such as natural factors and transportation, which are constant under every condition. It emphasizes once again the impact of planning decisions and policies on urban development. The driving factors chosen appropriately for the purpose simulate the cases of urban growth that may actually occur.

Since this study aims to observe driving factor effects over different scenarios, the scenarios created may be simpler than real planning projects. Planners, decision makers and the modelers should work together for a more detailed and comprehensive scenario study. It will be useful to simulate different scenario and driving factor combinations in future studies in order to see the complexity in more detail. The following studies will incorporate the change in land use demand according to the scenario and socio-economic factors. For a more comprehensive understanding of the regional dynamics, neighboring cities of Izmir will be added to the scenario based simulation. It is crucial to consider development scenarios which focus on geological and climatic problems such as earthquakes and the rise of sea level. In this direction, the points which have been ignored or not handled in sufficient detail due to the size of the geographical information should be investigated further with an interdisciplinary team.

As it can be seen from the research, simulation models are highly capable as decision support tools. The quality of studies in the field and the amount of validated urban models based on complexity theory show the necessity of incorporating them in real life urban planning applications. The combined use of planning applications and simulation models will rejuvenate and support the decision-making processes while improving the development and authenticity of models.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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